The interest rate spread as a forecasting tool of greek industrial production

Periklis Gogas and Ioannis Pragkidis

Democritus University of Thrace

March 2010

International Journal of Business Policy and Economics
Vol. 3, No. 1, (2010) : 37-46

THE INTEREST RATE SPREAD AS A FORECASTING TOOL OF GREEK INDUSTRIAL PRODUCTION

Periklis Gogas & Ioannis Pragidis
Democritus University of Thrace, Komotini, Greece

Several studies have established the predictive power of the yield curve, i.e.: the difference between long and short term bond rates, in terms of real economic activity, for the U.S. and various European countries. In this paper we use monthly data of the industrial production index of the Greek economy ranging from January 2000 to December 2008 and we calculate the year-to-year percentage change, while the European Central Bank's euro area government benchmark bonds of various maturities are employed for the calculation of the yield spreads. We also augment the models tested with non monetary policy variables: the Greek unemployment rate and the FTSE-100 stock index returns. The methodology employed in the effort to forecast negative year-to-year changes in the industrial production index is a probit model of the inverse cumulative distribution function of the standard distribution, using several formal forecasting and goodness of fit evaluation tests. The results show that the yield curve augmented with the composite stock index has significant forecasting power in terms of the industrial production in Greece.

JEL Classification: *E43, E44, E52, C53.*

Keywords: *Forecasting, Yield spread, Industrial production, Probit, Term structure, Monetary policy, Real growth, Greece.*

1. INTRODUCTION

The yield curve, measuring the difference between short and long term interest rates has been at the center of recession forecasting. The theoretical justification of this line of work is that since short term interest rates are instruments of monetary policy and long term interest rates reflect market's expectations on future economic conditions, the difference between short and longer term interest rates may contain useful information to policy makers and other individuals for the corresponding time frame. Furthermore, when the yield curve is upward slopping during recessions, it indicates that there are expectations for future economic upturn. On the other hand, just before recessions the yield curve flattens or even inverts. There are two major branches of empirical work in this area: first, simple OLS estimation where researchers try to predict future economic activity and second, probit models are used to forecast upcoming

* Corresponding Author: *E-mail: pgkogkas@ierd.duth.gr*

recessions. The main objective of these two classes of papers is to accommodate the fluctuations of future economic activity taking into account the information that is included in the yield curve and is independent of the exercised monetary policy. According to the influential paper in this line of research by Estrella and Mishkin (1997), the short end of the yield curve can be affected by the European Central Bank or the Federal Reserve or any other central bank, but the long end will be determined by many other considerations, including long term expectations of inflation and future real economic activity. In their paper, after taking into account monetary policy conducted in four major European countries (France, Germany, Italy and the U.K), they show that the term structure spread has significant predictive power for both real activity and inflation. Bonser and Morley (1997) after examining eleven developed economies found that the yield spread is a good predictive instrument for future economic activity. In the same vein, Venetis *et al*., (2003) reached the same conclusions as well as Hamilton and Kim (2002). On the other hand, Kim and Limpaphayon (1991) testing Japan, found evidence that the expected short term interest rate is the only source of predictability for Japan and not the term premium. Ang *et al*., (2005) after modeling regressor endogeneity and using data for the period 1952 to 2001, conclude that the short term interest rate has more predictive power than any term spread. They confirm their finding by forecasting GDP out of sample. There is also, a class of papers that use probit models to forecast recessions. Wright (2006) using as explanatory variables the federal reserve funds rate and the term spread forecasts recessions 6 quarters ahead for the U.S economy. Chauvet and Potter (2001), propose out of sample forecasting using standard probabilities as well as "hitting probabilities" of recession that take into account the length of the business cycle phases. They found, that standard probit specification that does not take into account the presence of autocorrelated errors and have time varying parameters due to existence of multiple breakpoints, tends to over predict recession results. In their paper Estrella *et al*., (2006) use recent econometric techniques for break-testing to examine whether the empirical relationships are in fact stable. They find that, models that predict real activity are somewhat more stable than those that predict inflation, and binary models are more stable than continuous models.

This paper, following the line of previous works using probit models, concentrates on the predictive power of the yield spread in the context of the Greek industrial production index. We concentrate on the industrial production index as reliable data for the quarterly Greek GDP are not available prior to 2000 leaving us with only forty observations. On the other hand, the industrial production index has a higher frequency as it is calculated on a monthly basis and the literature shows that it is a good proxy for overall economic activity and GDP. To the best of our knowledge, there hasn't been done any such analysis yet using the Greek industrial production. We also employ other real economy and financial explanatory variables as well, such as the FTSE-100 stock index and the rate of unemployment in Greece, in an effort to improve the predictive power of the model.

The rest of the paper is organized as follows: in section 2 we describe the data used, in section 3 we discuss the methodology we employ and present the empirical results and finally in section 4 we draw the conclusions for this study.

2. THE DATA

We measure economic activity in Greece in terms of the Greek industrial production index which is obtained from the Greek Statistics Agency web site monthly from 2001:1 to 2008:12. We restrict the analysis to this period as data availability and consistency issues arise for earlier data. The aim of this paper is to predict negative deviations of industrial production on a year-to-year basis and especially the probability that the industrial production of a particular month will be below last year's figure. For this reason, we calculate the year-to-year percentage change of the industrial production index as follows:

$$DI_t = \ln(IP_t) - \ln(IP_{t-12})$$

where IP is the industrial production index. Having extracted the year-to-year percentage change of the industrial production index we then construct its fluctuation dummy variable (PDI) that takes the value one whenever DI_t is negative indicating a negative growth of the industrial production index on a year-to-year basis and the value zero elsewhere. In Figure 1 we graph the year-to-year percentage change of the industrial production index. Our aim is to use the yield spread information and other explanatory variables in order to forecast negative values for the year-to-year percentage change of the industrial production index for Greece.

The explanatory variables we use are various yield spreads, the Greek unemployment rate and the FTSE-100 stock index returns of the London stock exchange. All interest rates used in calculating the yield spreads are extracted from the ECB statistics and are the interest rates for the euro area government benchmark bonds with maturities for the long term rates of one, five and ten years, and for the short term rates with maturities of one and three months.

Table 1
Descriptive Statistics for the Explanatory Variables

	PDI	*1-month*	*3-months*	*1-year*	*5-years*	*10-years*	*u*	*s*
Mean	0.55	0.67	3.40	3.56	3.93	4.41	9.69	−0.02
Median	1.00	0.58	3.35	3.60	3.85	4.32	9.85	0.06
Maximum	1.00	2.17	5.11	5.39	5.35	5.70	12.20	0.23
Minimum	0.00	0.40	2.03	2.01	2.58	3.16	7.20	−0.43
Std. Dev.	0.50	0.30	1.04	1.06	0.74	0.63	1.22	0.17
Skewness	−0.21	2.78	0.12	0.08	0.20	0.17	−0.28	−0.61
Kurtosis	1.04	11.67	1.58	1.65	2.09	2.22	2.43	2.22
Jarque-Bera	16.01	477.84	9.30	8.31	4.46	3.27	2.81	8.32
Probability	0.00	0.00	0.01	0.02	0.11	0.19	0.25	0.02
Sum	53.00	71.99	367.05	384.02	423.92	476.15	1046.40	−2.13
Sum Sq. Dev.	23.74	9.42	115.67	119.75	58.82	42.00	158.93	2.76
Observations	96	108	108	108	108	108	108	96

The Greek unemployment rate is obtained from the Greek Statistics Agency. Finally, the London FTSE-100 stock index is used as it is a leading European stock index and also as it appears to influence the regional European exchanges as well. The stock index data are obtained from Six Telekurs. In Table 1 we present a statistical summary of all the explanatory variables.

3. METHODOLOGY AND EMPIRICAL RESULTS

We consider seventy two alternative models for probit regressions forecasting a quarterly GDP cycle below trend at some point within the next h quarters:

$$prob\,(PDI_t = 1) = \Phi\,(\tilde{a}_0 + \tilde{a}_1\,(i_{LR,\,t-i} - i_{SR,\,t-i})], \quad i = 1, ..., h \qquad (1)$$

where PDI_t is the dummy variable that takes the value one every time the year-to-year percentage change of the Greek industrial production index negative and zero elsewhere. $\Phi(\cdot)$ denotes the standard normal cumulative distribution function, $(i_{LR,\,t-i} - i_{SR,\,t-i})$ represents the spread between the long and short run interest rates with $i = 1, ..., 12$. For the long run interest rates we use four rates alternatively, the one, five and ten year rates, while for the short run rates we use two alternatives, the one and three months maturities. Finally, $\tilde{a}_0$ and $\tilde{a}_1$ are the estimated parameters. Thus, equation (1) is estimated for all combinations of the short with the long run interest rates and forecast windows from one to twelve quarters ahead, a total of seventy two probit regressions. The estimated coefficient of the spread $\tilde{a}_1$, as it can be seen in Table 2 is statistically significant at probabilities $p < 0.1$ for twenty five out the total seventy two probit regressions with various combinations of yield spreads and forecast windows. For every combination of yield spread that we get a statistically significant estimated coefficient of the spread $\tilde{a}_1$, we then employ the *AIC* and *SIC* model selection criteria to select the best fit lag structure (forecast window) and thus we are left with the four models presented in columns one to four of Table 3. As the main purpose of this paper is the prediction of a negative year-to-year change in industrial production, next we formally compare the above four models in terms of their forecasting ability by calculating the root mean squared error (RMSE), mean absolute error (MAE), and the mean absolute percent error (MAPE) statistics. These statistics are calculated using the following formulas:

$$RMSE = \sqrt{\frac{1}{F}\sum_{f=1}^{F} e_{t+f}^2}$$

$$MAE = \frac{1}{F}\sum_{f=1}^{F} \left| e_{t+f} \right|$$

$$MAPE = \frac{1}{F}\sum_{f=1}^{F} \left| \frac{e_{t+f,t}}{y_{t+f}} \right|$$

Table 2
Probit Models' Estimation Statistics

Panel A. 1 Month Short-Term Rate

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*	*R-squared*	*AIC*	*SIC*	
Y1(-1)-M1(-1)	0.1813	0.1495	1.2125	0.2253	0.0112	1.4016	1.4551	
Y1(-2)-M1(-2)	0.2334	0.1473	1.5850	0.1130	0.0193	1.3906	1.4440	
Y1(-3)-M1(-3)	0.2400	0.1440	1.6672	0.0955	0.0213	1.3878	1.4412	
Y1(-4)-M1(-4)	0.2578	0.1423	1.8119	0.0700	0.0251	1.3825	1.4359	
Y1(-5)-M1(-5)	0.2931	0.1414	2.0729	0.0382	0.0330	1.3717	1.4252	
Y1(-6)-M1(-6)	0.3172	0.1414	2.2428	0.0249	0.0387	1.3639	1.4173	
Y1(-7)-M1(-7)	0.3641	0.1428	2.5488	0.0108	0.0503	1.3479	1.4013	
Y1(-8)-M1(-8)	0.4310	0.1454	2.9634	0.0030	0.0690	1.3221	1.3756	*
Y1(-9)-M1(-9)	0.4806	0.1485	3.2353	0.0012	0.0835	1.3022	1.3556	*
Y1(-10)-M1(-10)	0.5199	0.1511	3.4403	0.0006	0.0958	1.2854	1.3388	*
Y1(-11)-M1(-11)	0.5410	0.1527	3.5443	0.0004	**0.1025**	**1.2761**	**1.3295**	*
Y1(-12)-M1(-12)	0.5348	0.1524	3.5081	0.0005	0.1003	1.2791	1.3325	*
Y5(-1)-M1(-1)	0.0069	0.1977	0.0348	0.9722	0.0000	1.4171	1.4705	
Y5(-2)-M1(-2)	0.0932	0.1971	0.4727	0.6364	0.0017	1.4148	1.4682	
Y5(-3)-M1(-3)	0.2463	0.2002	1.2304	0.2186	0.0115	1.4013	1.4547	
Y5(-4)-M1(-4)	0.2600	0.1975	1.3169	0.1879	0.0132	1.3989	1.4524	
Y5(-5)-M1(-5)	0.2322	0.1922	1.2079	0.2271	0.0111	1.4018	1.4552	
Y5(-6)-M1(-6)	0.2151	0.1893	1.1367	0.2557	0.0098	1.4036	1.4570	
Y5(-7)-M1(-7)	0.1670	0.1850	0.9027	0.3667	0.0062	1.4086	1.4620	
Y5(-8)-M1(-8)	0.2251	0.1827	1.2326	0.2177	0.0116	1.4011	1.4546	
Y5(-9)-M1(-9)	0.1945	0.1782	1.0915	0.2750	0.0091	1.4046	1.4580	
Y5(-10)-M1(-10)	0.2125	0.1755	1.2106	0.2260	0.0112	1.4017	1.4551	
Y5(-11)-M1(-11)	0.2922	0.1754	1.6653	0.0959	0.0213	1.3877	1.4412	
Y5(-12)-M1(-12)	0.3477	0.1799	1.9325	0.0533	0.0290	1.3772	1.4306	
Y10(-1)-M1(-1)	–0.0274	0.2168	-0.1264	0.8994	0.0001	1.4169	1.4703	
Y10(-2)-M1(-2)	0.0287	0.2187	0.1314	0.8954	0.0001	1.4169	1.4703	
Y10(-3)-M1(-3)	0.0095	0.2211	0.0429	0.9658	0.0000	1.4171	1.4705	
Y10(-4)-M1(-4)	0.0290	0.2173	0.1333	0.8940	0.0001	1.4169	1.4703	
Y10(-5)-M1(-5)	0.0777	0.2138	0.3632	0.7165	0.0010	1.4157	1.4691	
Y10(-6)-M1(-6)	0.0327	0.2107	0.1552	0.8767	0.0002	1.4168	1.4703	
Y10(-7)-M1(-7)	0.1191	0.2085	0.5711	0.5680	0.0025	1.4137	1.4671	
Y10(-8)-M1(-8)	0.2508	0.2074	1.2094	0.2265	0.0112	1.4017	1.4552	
Y10(-9)-M1(-9)	0.3159	0.2067	1.5280	0.1265	0.0179	1.3924	1.4459	
Y10(-10)-M1(-10)	0.4044	0.2066	1.9573	0.0503	0.0296	1.3763	1.4298	
Y10(-11)-M1(-11)	0.4539	0.2042	2.2228	0.0262	0.0384	1.3643	1.4177	
Y10(-12)-M1(-12)	0.4118	0.2021	2.0374	0.0416	0.0321	1.3729	1.4263	

An asterisk denotes significance at 1% level.

Statistics in bold denote the value of the maximized McFadden R^2 and the minimized *AIC* and *SIC*.

Table 2 (Continued)
Probit Models' Estimation Statistics

Panel B. 3 Month Short-Term Rate

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*	*R-squared*	*AIC*	*SIC*	
Y1(Y1(-1)-M3(-1)	−1.6248	0.6722	−2.4173	0.0156	0.0459	1.3539	1.4074	
Y1(-2)-M3(-2)	−1.8106	0.6803	−2.6616	0.0078	0.0561	1.3399	1.3933	*
Y1(-3)-M3(-3)	−2.2122	0.7028	−3.1477	0.0016	0.0806	1.3063	1.3597	*
Y1(-4)-M3(-4)	−2.3145	0.7071	−3.2732	0.0011	0.0876	1.2966	1.3500	*
Y1(-5)-M3(-5)	−2.3988	0.6938	−3.4574	0.0005	**0.0971**	**1.2836**	**1.3370**	*
Y1(-6)-M3(-6)	−2.1869	0.6760	−3.2349	0.0012	0.0839	1.3017	1.3552	*
Y1(-7)-M3(-7)	−1.7303	0.6572	−2.6330	0.0085	0.0545	1.3421	1.3955	*
Y1(-8)-M3(-8)	−0.7482	0.6202	−1.2063	0.2277	0.0111	1.4018	1.4553	
Y1(-9)-M3(-9)	0.0661	0.6100	0.1083	0.9137	0.0001	1.4170	1.4704	
Y1(-10)-M3(-10)	0.8782	0.6087	1.4426	0.1491	0.0159	1.3952	1.4487	
Y1(-11)-M3(-11)	1.3797	0.6089	2.2659	0.0235	0.0398	1.3624	1.4158	
Y1(-12)-M3(-12)	1.6851	0.6028	2.7952	0.0052	0.0611	1.3330	1.3865	*
Y5(-1)-M3(-1)	−0.3713	0.1812	−2.0495	0.0404	0.0328	1.3720	1.4254	
Y5(-2)-M3(-2)	−0.4145	0.1859	−2.2301	0.0257	0.0393	1.3631	1.4165	
Y5(-3)-M3(-3)	−0.3645	0.1893	−1.9252	0.0542	0.0288	1.3775	1.4309	
Y5(-4)-M3(-4)	−0.4207	0.1975	−2.1304	0.0331	0.0357	1.3680	1.4214	
Y5(-5)-M3(-5)	−0.5587	0.2085	−2.6795	0.0074	0.0581	1.3372	1.3906	*
Y5(-6)-M3(-6)	−0.6233	0.2131	−2.9256	0.0034	0.0702	1.3206	1.3740	*
Y5(-7)-M3(-7)	−0.7577	0.2249	−3.3689	0.0008	**0.0969**	**1.2838**	**1.3372**	*
Y5(-8)-M3(-8)	−0.7307	0.2282	−3.2018	0.0014	0.0876	1.2967	1.3501	*
Y5(-9)-M3(-9)	−0.7830	0.2369	−3.3059	0.0009	0.0957	1.2854	1.3389	*
Y5(-10)-M3(-10)	−0.7100	0.2305	−3.0797	0.0021	0.0803	1.3066	1.3600	*
Y5(-11)-M3(-11)	−0.5572	0.2249	−2.4781	0.0132	0.0502	1.3481	1.4015	
Y5(-12)-M3(-12)	−0.4520	0.2248	−2.0104	0.0444	0.0321	1.3730	1.4264	
Y10(-1)-M3(-1)	−0.3036	0.1579	−1.9229	0.0545	0.0287	1.3777	1.4311	
Y10(-2)-M3(-2)	−0.3584	0.1609	−2.2271	0.0259	0.0388	1.3637	1.4171	
Y10(-3)-M3(-3)	−0.4290	0.1662	−2.5808	0.0099	0.0527	1.3446	1.3980	*
Y10(-4)-M3(-4)	−0.4700	0.1692	−2.7782	0.0055	0.0611	1.3330	1.3865	*
Y10(-5)-M3(-5)	−0.5286	0.1748	−3.0245	0.0025	0.0733	1.3163	1.3697	*
Y10(-6)-M3(-6)	−0.6108	0.1816	−3.3626	0.0008	**0.0926**	**1.2898**	**1.3432**	*
Y10(-7)-M3(-7)	−0.5979	0.1823	−3.2801	0.0010	0.0875	1.2968	1.3502	*
Y10(-8)-M3(-8)	−0.5454	0.1841	−2.9620	0.0031	0.0707	1.3199	1.3733	*
Y10(-9)-M3(-9)	−0.5096	0.1869	−2.7265	0.0064	0.0595	1.3353	1.3887	*
Y10(-10)-M3(-10)	−0.4260	0.1866	−2.2837	0.0224	0.0409	1.3608	1.4142	
Y10(-11)-M3(-11)	−0.3570	0.1859	−1.9204	0.0548	0.0287	1.3777	1.4311	
Y10(-12)-M3(-12)	−0.3467	0.1867	−1.8566	0.0634	0.0268	1.3803	1.4337	

An asterisk denotes significance at 1% level.

Statistics in bold denote the value of the maximized McFadden R^2 and the minimized *AIC* and *SIC*.

where $e_{t+f} = y_{t+f} - y^*_{t+f}$ and y_{t+f} is the actual value of the series at period $t + f$, y^*_{t+f} is the forecast for y_{t+f} and F is the forecast window. These statistics are summarized in Table 3. We see that model 1, the one constructed with the spread of the one year interest rate minus the one month interest rate and at forecast window of eleven quarters, outperforms in terms of forecasting efficiency all four other models and for all three forecasting criteria. Moreover, we report in the last column of Table 3 the McFadden R^2 for each model and this is maximized again for the model employing the one year interest rate minus the one month interest rate and at forecast window of eleven quarters. The value of 0.1025 for the McFadden R^2 is considered a satisfactory fit as this statistic tends to be smaller than standard R^2. Thus, for the rest of the paper we employ this model for the purposes of estimating the probability that the year-to-year change in industrial production will be negative. Next, in an effort to examine whether other variables from the real economy can add any informational content to the forecasts of the year-to-year change in industrial production we estimate the following probit regressions:

$$prob\,(PDI_t = 1) = \Phi\,(\tilde{a}_0 + \tilde{a}_1\,(i_{LR,\,t-i} - i_{SR,\,t-i}) + \tilde{a}_u\,u_{t-i}] \tag{2}$$

$$prob\,(PDI_t = 1) = \Phi\,(\tilde{a}_0 + \tilde{a}_1\,(i_{LR,\,t-i} - i_{SR,\,t-i}) + \tilde{a}_s\,s_{t-i}], \tag{3}$$

Table 3
Forecasting Model Selection Criteria

	Predicting Spread			*Forecasting Criteria*							
Model	*Long term rate*	*Short term rate*	*Forecast window*	*RMSE*		*MAE*		*MAPE*		*McFadden R^2*	
1	1 year	1 month	11 months	0.4639	*	0.4287	*	21.3933	*	0.1025	*
2	1 year	3 months	5 months	0.4648		0.4316		21.5962		0.0971	
3	5 years	3 months	7 months	0.4677		0.4345		21.4977		0.0969	
4	10 years	3 months	6 months	0.4680		0.4357		21.6203		0.0926	

An asterisk denotes the minimized value for the forecast evaluation criteria and the maximumMcFadden R^2.

where u_t is the unemployment rate for Greece, s_t is the returns on the FTSE-100 index, $i = 11$ and $\tilde{a}_u$, $\tilde{a}_s$ are their estimated coefficients. As we can see in Table 4, the unemployment as an explanatory variable is not statistically significant at probability 0.05. From Table 5 we see that the inclusion of the FTSE-100 stock index returns as an explanatory variable is statistically significant for probability 0.05. Thus, we then compare the forecasting power of the previously selected model 1, the one constructed with the spread of the one year interest rate minus the one month interest rate and at forecast window eleven quarters and the same spread and lag structure with the inclusion of the FTSE-100 stock index returns variable. The forecasting error statistics of the two compared models are presented in Table 6 along with the McFadden R^2. According to all four statistics the model with the FTSE-100 stock index returns variable is selected in terms of forecasting accuracy and goodness of fit. In Figure 2, we graph the

Table 4
Probit Estimation with Unemployment as an Explanatory Variable

Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
u_{t-11}	−0.248	0.142	−1.749	0.080

Table 5
Probit Estimation with the Stock Index as an Explanatory Variable

Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*	
s_{t-11}	1.89939	0.933	2.036	0.042	*

An asterisk denotes significancy at the 5% level.

Table 6
Forecasting Model Selection Criteria

Predicting Spread				*Forecasting Criteria*							
Long term rate	*Short term rate*	*Forecast window*	*Stock Index*	*RMSE*		*MAE*		*MAPE*		*McFadden R^2*	
1 year	1 month	11 months	no	0.4639		0.4287		21.3933		0.1025	
1 year	1 month	11 months	yes	0.4595	*	0.4224	*	21.1624	*	0.1169	*

An asterisk denotes the minimized value of the criterion.

forecasted probability of a negative year-to-year industrial production growth using the best fit model already selected along with the Greek year-to-year percentage change in the monthly industrial production index. As it can be seen

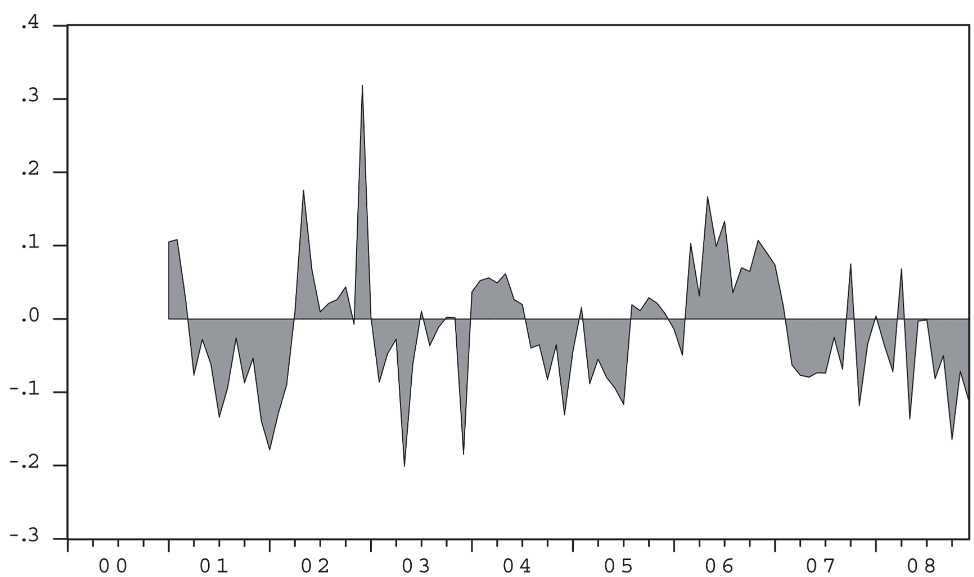

Figure 1
Year-to-Year Percentage Change of the Industrial Production Index

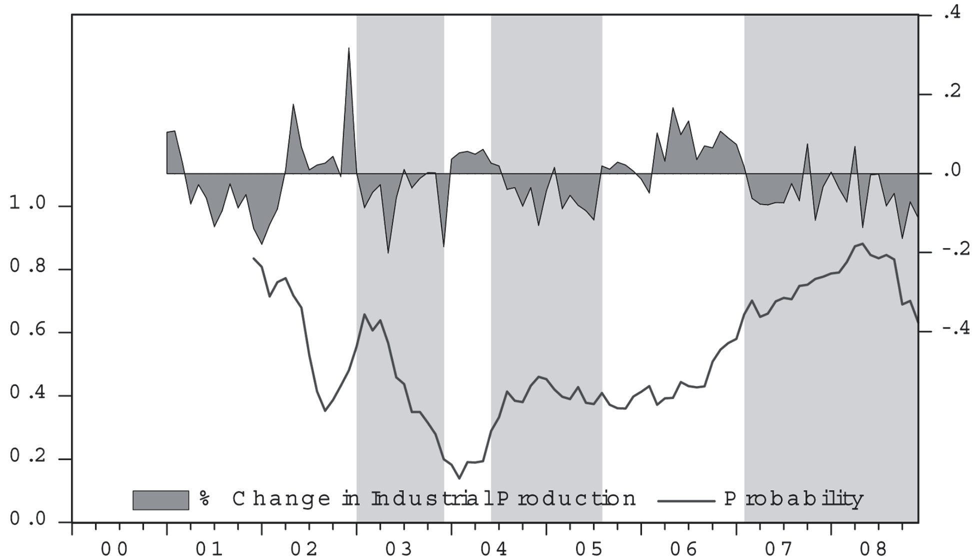

Figure 2
Forecasted Probability of Negative Year-to-Year Industrial Production Change

in Figure 2, the predictive power of the estimated model in terms of the forecasted probabilities of negative deviations of the industrial production index is high. It seems that the yield spread between the one year and the one month euro area government benchmark bonds augmented with the FTSE-100 stock index returns and a forecast window of eleven quarters ahead is a very good predictor of the fluctuation of the Greek industrial production.

4. CONCLUSIONS

In this paper we have used several probit models to examine the power of the yield spread between various long term and short term maturities of euro area benchmark bonds in predicting the year-to-year percentage change in the monthly industrial production index. Our results show that the yield spread of relatively short term interest rates dominates in terms of forecasting efficiency the yield spread of longer term interest rates. Moreover, we have included in the estimation models both the Greek unemployment rate and the FTSE-100 stock index returns in an effort to investigate whether other than monetary policy variables can add any forecasting power to the yield spread. The results, after the formal evaluation of the forecasting ability of the different yield spreads and in different forecast horizons show that the best model is the one employing the spread between relatively short term interest rates, the one year and the one month euro area benchmark bonds with a forecast horizon equal to eleven quarters ahead. These results come in line with the findings of Ang et al (2005) that short rates have more predictive power than any term spread. The inclusion of unemployment in the best yield spread model was not statistically significant at any forecast horizons. The FTSE-100 stock index on the other hand was statistically significant and according to the formal forecasting evaluation tests improved the ability of the model to predict negative year-to-year percentage changes in the monthly industrial production index in Greece. Overall, the final model used for forecasting appears very efficient to forecast deviations of the real output from the long run trend according to the standard formal goodness of fit tests employed.

References

Ang A., Piazzesi M., and Wei M., (2006), "What Does the Yield Curve Tell us About GDP?", *Journal of Financial Econometrics*, 131: 359-403

Bonser-Neal Catherine, and Timothy R. Morley, (1997), "Does the Yield Spread Predict Real Economic Activity? A Multicountry Analysis", Federal Reserve Bank of Kansas City, *Economic Review*, Third Quarter.

Chauvet M., and S. Potter, (2001a), "Predicting a Recession: Evidence from the Yield Curve in the Presence of Structural Breaks", *Working Paper*, University of California, Riverside.

Cogley T., and J. M. Nason., (1995), Effects of the Hodrick-Prescott Filter on Trend and Difference Stationary Time Series: Implications for Business Cycle Research, *Journal of Economic Dynamics and Control*, 254.

Estrella, and Mishkin, (1996), "The Term Structure of Interest Rates and Its Role in Monetary Policy for the ECB", *Working Paper No. 5279*, (NBER, Cambridge, MA) Sept.

Estrella, and Hardouvelis, (1991), "The Term Structure as a Predictor of Real Economic Activity", *Journal of Finance*, 46(2), June.

Estrella, and Mishkin, (1997), "The Predictive Power of the Term Structure of Interest Rates in Europe and the U.S: Implications for the ECB", *European Economic Review*, 41: 1375-1401.

Feitosa M. A., and Tabak B. N., (2007), "Predictability of Economic Activity Using Yield Spreads: The Case of Brazil", Anais do XXXV Encontro Nacional de Economia, *Proceedings of the 35th Brazilian Economics Meeting*, 029.

Hodrick R., and E. P. Prescott, (1997), "Postwar Business Cycles: An Empirical Investigation," *Journal of Money*, Credit, and Banking.

Kim A., and Limpaphayom P., (1997), The Effect of Economic Regimes on the Relation between Term Structure and Real Activity in Japan, *Journal of Economics and Business*, 49: 379-392.

Marcelle Chauvet, and Simon Potter, (2005), "Forecasting Recessions using the Yield Curve", *Journal of Forecasting*, John Wiley & Sons, Ltd., 24(2): 77-103.

Nakota H., (2005), "The Term Structure of Interest Rates in Japan: The Predictability of Economic Activity", *Japan and the World Economy*, 17: 311-326.

Venetis I. A., Paya I., and Peel D. A., (2003), "Re Examination of the Predictability of Economic Activity using the Yield Spread: A Non Linear Approach", *International Review of Economics and Finance*, 12: 187-206.

Wright J., (2006), "The Yield Curve and Predicting Recessions", *Finance and Economics Discussion Series*, 2006-7, Federal Reserve Board.